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An Intelligent Deep Learning Framework for Early Detection of Alzheimer Disease Using Temporal Fusion CNN

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ABSTRACT: Brain disease is a wide range of disorder that harm brain structure which leads to the disorders such as memory loss, problems that deals with thinking, emotional stress, misbehavior, changes in daily activities of a human being. This paper proposes K-means clustering based Grey Level Co-occurrence Matrix (GLCM) feature extraction with temporal fusion Convolution Neural Networks (CNN) to detect alzheimer's disease and different disease trajectories. The term Alzheimer disease refers to brain disorder that destroys memory and rational expertise. The K- means clustering process is used to identify groups of similar data points and helps in anomaly detection. The feature extraction of GLCM analyses the relationship between pixels for capturing images which is applicable in medical diagnosis. A deep learning technique that integrates CNN to process input data, such as images or video frames, to extract important spatial features. This research significantly improves the health care system and assist as a valuable diagnostics tool in medical field and helps healthcare professionals in diagnosing alzheimer's disease. According to the experimental outcomes attained from relevant software tool the overall accuracy is 95% and precision, recall scores as 96% respectively.

Keywords: Alzheimer's disease detection, Data preprocessing, K-means clustering, GLCM feature extraction, Classification-Temporal fusion CNN.

1. Introduction

The name Alzheimer's comes from Alois Alzheimer a German neuropathologist who identified the specific pathological features. Alzheimer is a brain sickness progressively impairs memory and intellectual skills of patient. The diagnosis of such disorder is exciting, chiefly in the early stages of rising cognitive failure. [1]. A deep learning approach using convolution autoencoders has a very interesting feature that exemplary a dataset in a self-managed mode, effectively useful to psychiatry and breast cancer. The autoencoder is trained with each tissue dataset that describes a novel gap to which the brain maps projected from their original image space. However, the link among experiment grades, and physical variations in the brain, which are serious to legalizing analyzes [2]. Mild cognitive impairment (MCI) is currently incurable, therefore 18F-FDG PET imaging method, active in sensing metabolic actions in brain, which confuses the abstraction of essential lesion evidence is active for early stage MCI diagnose. A deep learning based model lessens overfitting, advances simplification, and enriches the discovery of subtle metabolic changes and thereby overcoming those challenges [3]. Transcranial alternating current simulation (tACS) use reduction of field potentials and abnormal connection between the hippo-campus and the prefrontal cortex subsidize to the decline in short-term memory act in Alzheimer's disease. However, due to the presence of cerebrospinal fluid, skin and other tissues, the current flows to the tissues with low impedance. Since the right hippocampus is close to electrodes, it accepts a moderately robust electric field. The left hippocampus and prefrontal cortex only accept an electric field below 1 V/m [4]. Dual-3DM3-AD model involves a multi-scale feature extraction module, that excerpts relevant structures from segmented images. It confirms critical info from images efficiently seized and an accumulation progression exploits use of info from scan. However, it involves several hidden layers, large conjunction masses, and lengthy calculation times, leads to sharp difficulty and a possible discount in classification precisions [5]. Alzheimer's prediction using audio transcript further revealed by hybrid swarm intelligence (HSI) based Linguistic feature selection (LFS) which reduces multi-collinearity and overfitting standard from dataset. It uses adaptive height apprises to learn a ranked prototypical talented of noticing and categorizing high-level labels in any two-dimensional space [6]. A Deep Continual Learning for Alzheimer's disease Stage Identification (CLADSI) system is developed to execute a continual learning process for identification of Alzheimer's disease. This method follows initialization, initial training, data collection, constrain optimization and performance evaluation. However, it is essential to recognize that accelerometers meet concerns and irregularities, as they are not much progressive as the devices used in specialized movement study laboratories which are directly attached to the body [7]. A Leveraging Neural Processing and encoder model for disease progression for modelling the complex temporal dependence characteristic in longitudinal health data, where it absorbs to capture delicate patterns and distinction figurative of disease evolution. Although the model demonstrates enhanced performance in the classification task compared to other methods, in accurately identifying all prediction classes [8]. A temporal domain features extracted from EEG signals effectively find typical neurophysiological designs associated with dementia. It enables accurate differentiation between dementia subtypes. Dual-Stream Deep Learning (DL) Gradual Variation outline for Spatial Feature Enhancement with measurement drop to address trials in attaining better presentation due to complications in catching compound longitudinal topographies and hold high-dimensional data. However efficiently extracted prominent features and reduced computational complexity, resulting in high classification accuracy [9-10].

Henceforth in this paper the limitation faced in traditional methods is succeeded, by introducing a deep learning techniques for Early detection of Alzheimer's disease based on CNN temporal fusion classification.

2. Recent Works

Xiao Zhou *et al* [2024] [11] have introduced adversarial learning for MRI reconstruction. The research focuses on attaining single tasks including refining image resolution, segmenting images, and adjusting signal objects on dementia. The excellence of MRI scan, determines mostly by scanner itself, which plays a significant role in precisely suggesting regions affected by disease. MRIs are chosen to reduce the time and the framework to see twin goals even when its learning ability is essentially incomplete due to hardware and sample size. However, MRIs necessitate long acquirement times, leads to patient uneasiness and motion artifacts.

Yu-Nong Lin *et al* [2025] [12] have proposed a dual approach of MRI-Positron Emission Tomography (PET) for brain enhancing the structural details and quantitative accuracy of FDG-PET, which is tainted by partial volume effects (PVE). It reliance on prior segmentation for an optimal performance expectations about tracer activity to produce alternative anatomical input. Nevertheless glucose metabolism varies among different diagnostic groups then extra varied medical tasks to legalize the exactitude.

Erol Kina *et al* [2025] [13] have developed trivial convolutional architecture created on efficient net with a crush consideration block using transfer learning. It utilizes synthetic minority oversampling methodology to address the disputes of detection of alzheimer's disease overfitting and unfair examples by balancing two expressively unwarranted MRI datasets with robustness but basic structure offers manageable timing with computational complexity, and additional memory requirements.

Mumine Kaya Keles *et al* [2022] [14] have presented a binary version of bee colony algorithm for classification determine Alzheimer's disease. The contrast among conventional data mining algorithms and bee colony shows dominance in footings of accuracy and F1-measure. Three classifiers, specifically KNN, RF, and SVM, are engaged separately in a dual appliance of procedures. However it has limited sample size and ill-starred for gaining proper and necessary health records for this investigation is one of the greatest problematic measures of the study.

Rabia Javed *et al* [2025] [15] have offered chronic disease prediction that contributes to enhance the healthcare 5.0 by developing an Internet of Medical Things (IoMT) for accurate prediction of long-lasting disease like Alzheimer's. The concept of spatial attributes and capturing temporal associations is developed by transfer learning. Nonetheless, an hesitation about association amid such healthy lifestyle, especially disease-free life anticipation, public conception and rule statement than broadly used virtual risk evaluations.

The proposed research helps in early detection of Alzheimer's disease using difference of Gaussians preprocessing of K-means cluster segmentation with GLCM feature extraction under temporal CNN classification technique.

The following are the papers' primary contributions:

- The diagnosis of Alzheimer's disease preprocessing is carried out by input images using difference of Gaussians.
- The segmentation process involves using image processing techniques particularly from MRI-scans to identify specific brain regions and tissues affected by the disease.
- K-means clustering used to detention meaningful structure, primary processes, and grouping intrinsic in a dataset.
- Feature Extraction is performed to extract meaningful numerical features from the segmented regions. Here, GLCM is specified, a statistical method for texture analysis that quantifies the transition of image between two neighboring pixels.
- The extracted features are then fed into classification stage which uses a Temporal fusion CNN classification which suggests the input includes temporal data.

3. Proposed system

Alzheimer's disease is not a single factor but a complex combination of factors, including the gradual build-up of abnormal proteins in the brain, which damages neurons and leads to cell death.

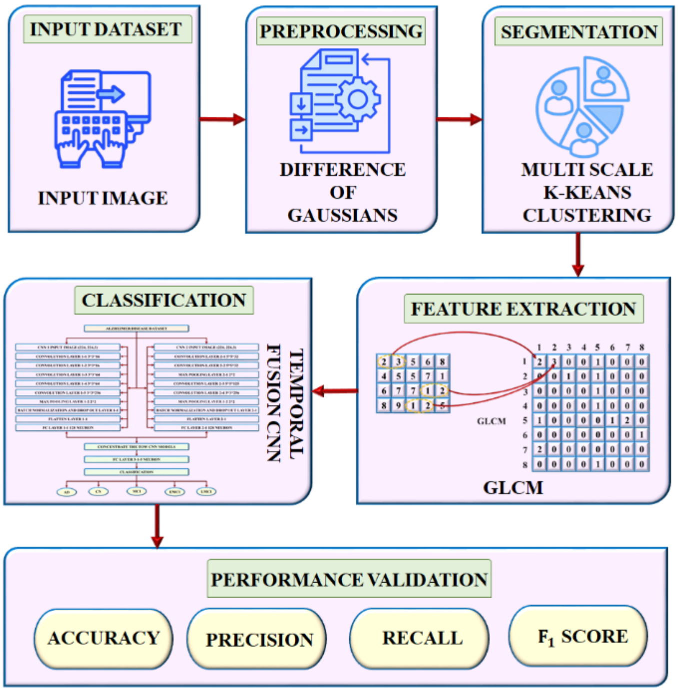

Figure 1: *Proposed block diagram*

The block diagram is shown in Figure 1. An input dataset consist of medical images or brain signals from the patients is categorized as MCI or Alzheimer's disease. The determination of preprocessing is to clean and enhance the data for better analyzing. The technique often used in image processing, helps improving the edges and details by subtracting two Gaussian blurred visions of an image with different standard versions. The segmentation process is used to isolate the regions of interest within an image or signal which is applicable for diagnosis. A multi-scale K-means algorithm used to group pixels bunches centered on its features in segmenting brain structures which is related to Alzheimer's disease. The feature extraction that derives the quantitative features from segmented data between healthy and diseased states. Here GLCM method is used in image processing to excerpt arithmetical features that define the texture of a region, which is useful in identifying subtle changes in brain tissue in MRI images associated with alzheimer's disease. An extracted features are then fed into a classifier to distinguish between healthy brains and those exhibiting signs of Alzheimer's disease. "Temporal Fusion CNN specifies a deep learning approach that analyze sequential or multi-modal data and learn complex patterns for accurate classification of Alzheimer's stage. The final stage is the predicted output by classifying the input data that shows the signs whether it is Alzheimer's disease or not, hypothetically sustaining in early detection and invention strategies.

4. Proposed System Modelling

The Input Dataset consist of MRI brain images from individuals, potentially including both healthy subjects and those with varying stages of Alzheimer's disease.

4.1 Difference Gaussians Preprocessing

A specific technique used within preprocessing often for edge detection or enhancing fine details. It involves subtracting two Gaussian-blurred versions of image, each with a different standard deviation, to highlight features present at certain scales.

In general distribution functions which is indicated by its mean (m) and covariance (k) in Gaussian method.

$$f(x) \sim GP\big(m(x), k(x, x')\big) \qquad (1)$$

Gaussian technique frequently used in image processing by subtracting Gaussian blurred version of an image with different standard deviation.

Gaussian process is a non-parametric simplification of linear reversion that is described for training data $D = \{(X_i, y_i)\}_{i=1}{}^{n}$ as given by

$$y_i = f(x_i) + \epsilon_i,\ \epsilon_i \sim N(0, \sigma^2) \qquad (2)$$

$f(x)$ is the knowledge about memory score in various locations, x is brain morphometric and covariate feature space individual differences.

$$m(x) = E[f(x)]$$

$$k(x, x') = E\big[\big(f(x) - m(x)\big)\big(f(x') - m(x')\big)\big] \qquad (3)$$

The robustness of Gaussian process is dependent on the choice of covariance function and its parameters.

4.2 Multiscale K-means clustering Segmentation process:

K-means clustering is an unverified clustering algorithm used to group pixels or data points into clusters which helps in finding distinct patterns in Alzheimer's disease. It is widely to divide data into k clusters. Thus, k-means algorithm wishes to distinct data into similar groups thru mutual appearances. The clusters created as given by:

$$arg \min_{c} \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|^2 \qquad (4)$$

$$V = \sum_{i=1}^{k} \frac{1}{|C_i|} \sum_{x \in C_i} \left\| x - \frac{1}{|C_i|} \sum_{x \in C_i} x \right\|^2 \qquad (5)$$

The set of comments $(x_1, x_2, \ldots, x_n)$, , k-means targets to screen n remarks into $k\ (\leq n)$ sets $S = \{S1, S2, \ldots, S_k\}\ or\ C = \{C1, C2, \ldots, C_k\}$ to diminish sum of squares or variances, where μ_i is mean of points in cluster C_i.

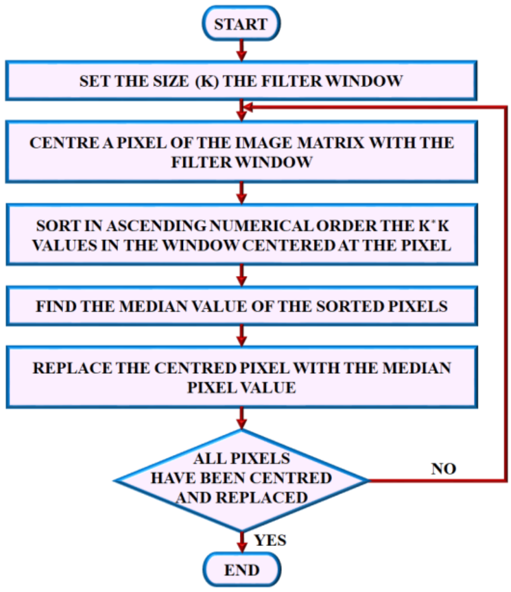

Figure 2: *Flowchart of K-means clustering*

Figure 2 shows K-means organization chart. The k-means is a un-predictable that means outcome of clustering is dissimilar each time, algorithm is track, even on equal dataset. The resultant segmentation characterizes the cerebrospinal fluid, white matter and gray matter covering the hippocampus and amygdala.

4.3 GLCM Feature Extraction:

The texture possessions from images is recovered using this feature extraction. It characterizes full grayscale image stages details on nearby direction. In GLCM, a normal erection stuff is contrast (CON), energy (ASM), entropy (ENT) and correlations (COR). The matrix gray stage is shown in figure 3

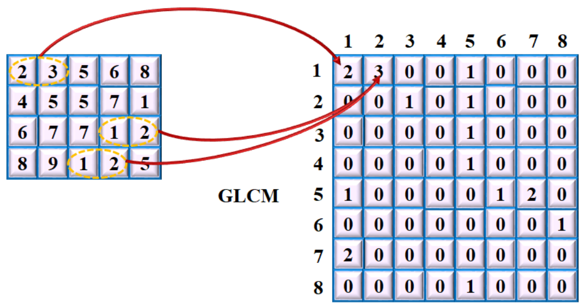

Figure 3: *Co-occurrence matrix of gray stage*

The quality of image and texture signifies contrast (CON)

$$CON = \sum i \sum_j (i - j)^2 \cdot p(i, j) \qquad (6)$$

ASM denotes the degree of image's shift in grey texture.

$$ASM = \sum i \sum_j p(i,j)^2 \qquad (7)$$

Dimension of column and row values assumption is named Correlation (COR).

$$COR = \frac{\sum i \sum_j (i,j) \cdot p(i,j) - \mu_i \mu_j}{\sigma_i \sigma_j} \qquad (8)$$

Entropy is a design knowledge that signifies an range of consistent disparities in aspect on image texture.

$$ENT = -\sum i \sum_j p(i,j).\log p(i,j) \qquad (9)$$

The inverse distance signifies an image texture documentation of various part of frame.

$$Inverse\ distance = \sum i \sum_j \frac{p(i,j)}{1+(i-j)^2} \qquad (10)$$

Therefore, the grey image equal to first basic in GLCM intentions and also restrained to rise the dimension act and to condense the geometric trouble.

4.4 Temporal Fusion CNN Classification:

To perform diverse patient data, creating a network including two separate CNN models, the temporal dimension assists as an input for the network. It begins with convolutional layers, each comprising 32 filters of size. Lastly, a fully linked layer with 128 neurons is attached to glean global visions since the compressed feature maps.

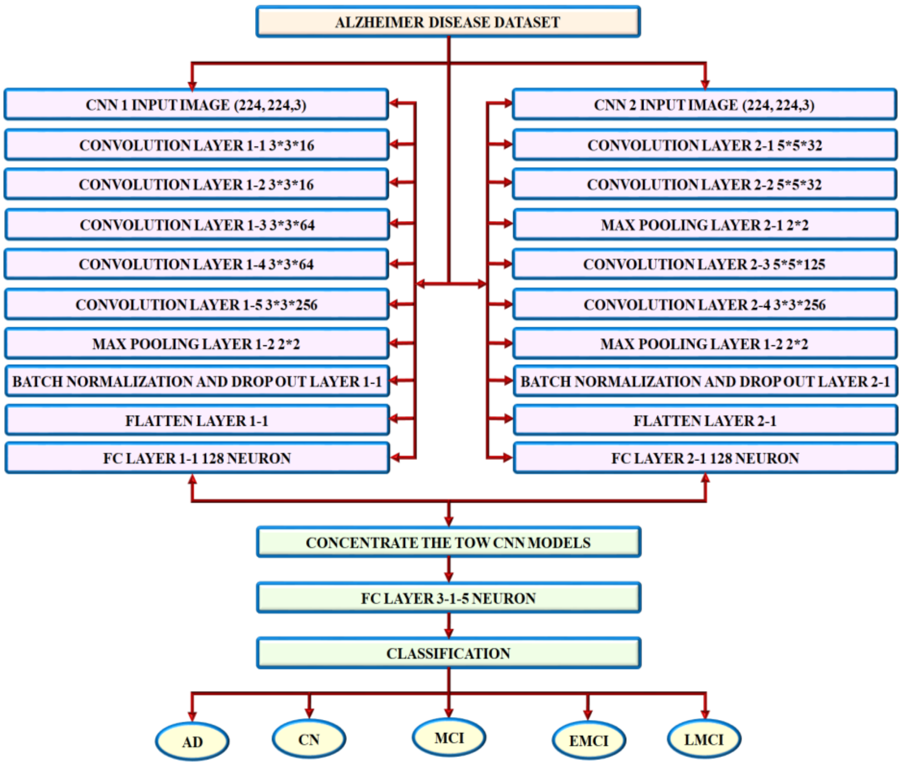

Figure 4: *Flowchart of Temporal fusion CNN*

A ensuing rotund of max-pooling is performed for three-dimensional fall. The input fits any of five classes, produced by structures extracted from each CNN network and dispensation the results on a fully connected network. Various modifications are assessed to begin the fitness of altered layers and convinced hyper parameters applied in the network. These assessments included batch regularization, numerous failure taxes, and varied pooling systems.

Consequently, final output is the classification result, demonstrating whether an input brain image shows signs of Alzheimer's disease, potentially along with an output image emphasizing affected areas or providing a probability map.

5. Results and discussions

The overall results are obtained using Python Software which is used in various simulation and experimental results. Accordingly this research helps in diagnosing early stage revealing of Alzheimer's disease using temporal fusion CNN technique.

Table 1: *Dementia Severity Stages*

Class	Stages
Class1	Mild demented
Class2	Moderate demented
Class 3	Non-demented
Class4	Very mild demented

The table 1 shows the dementia severity stages commonly used in medical imaging and machine learning applications for diagnosing and categorizing of Alzheimer's disease. There are four stages which is determined as mild demented that indicates the cognitive and functional impairments potentially affecting daily life in subtle ways. Moderately demented stage which presents more significant level requiring great assistance with daily activities. Non-demented shows the individuals who do not exhibits signs of dementia are considered cognitively normal. Very mild demented describes the stage where the symptoms not yet severe enough for a formal dementia diagnosis.

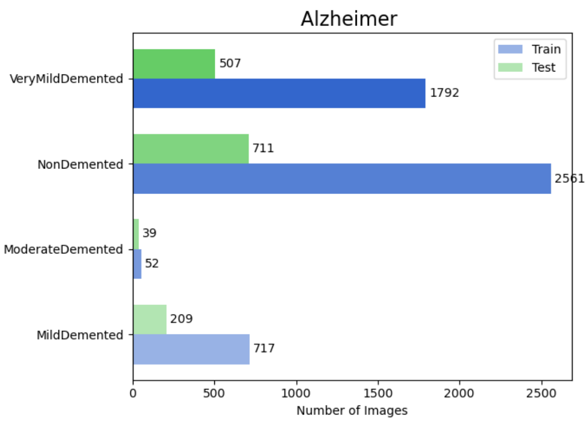

Figure 5: *Bar chart of Alzheimer stages*

Figure 5 displays the bar titled Alzheimer that visualizes the distribution of image count across different stages of dementia for both testing and training databases. For each dementia stage the number of images allocated for Train indicated in blue line and Test in green line. The Non-demented category has the highest number of images with 2561 and 751 for each. Very mild demented has 1792 training images and 507 testing images. Accordingly mild demented consist of 717 and 209 images. Similarly moderate demented has the lowest image with 52 and 39 respectively.

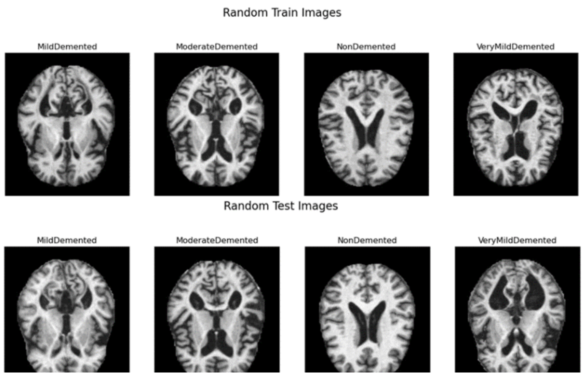

Figure 6: *Random Train and Test Images*

Figure 6 represents the random train and test images of dementia. The random train images which are brain scans categorized for the detection alzheimer's disease. This type of images are used in dataset that offers neuro-imaging data for dementia. The image serves an input for training algorithms which establishes the different stages of dementia and enabling automated classification and diagnosis.

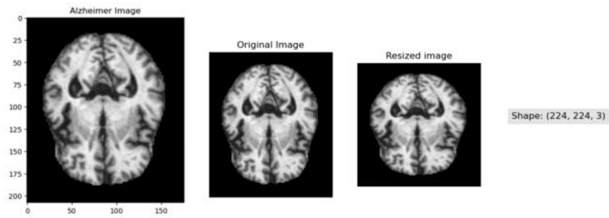

Figure 7: *Original and resized Alzheimer Images*

Figure 7 shows the input, original and resized images of Alzheimer. The original and resized image of a brain scan accompanied by the shape (224, 224, 3). It represents the height and width of images in pixels, also the number of color channels typically corresponding to red, green, and blue channels for color image.

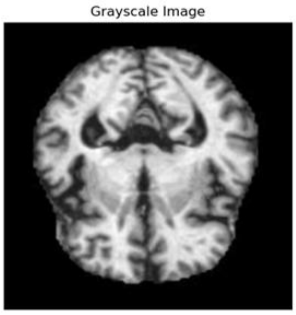

Figure 8: *Grayscale Alzheimer Images*

Figure 8 illustrates the grayscale Alzheimer Images. The grayscale image is a representation of an image where color information is removed and ranges from black to white. In medical ranging especially for MRI, CT and X-ray greyscale images is crucial.

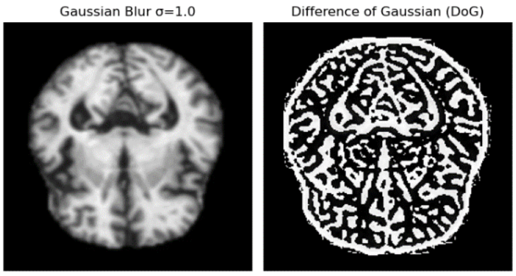

Figure 9: *Gaussian blur and difference of Gaussian Images*

The Gaussian blur and difference Gaussians Images is shown in figure 9. The image demonstrates the applications of two common image processing techniques to a brain MRI scan. The Gaussian blur $\sigma = 1.0$ is a smoothed version of original brain MRI. It is a low pass filter primarily used for noise reduction and image smoothing. The difference of Gaussian is a binary image highlighting the intensity changes in brain MRI. It involves subtracting two Gaussian-blurred versions of an image. The subtraction effectively creates a band-pass filter that enhances the features like edged and spots. In medical imaging the edge detection which helps in tasks like tumor detection or segmentation.

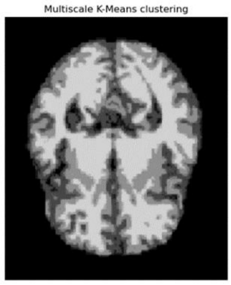

Figure 10: *Multiscale K-means clustering*

Figure 10 displays the Multiscale K-means clustering which is an image processing technique used to segment and analyze image data at various levels of resolutions. It involves iteratively assigning pixels (voxels in 3D images) to the nearest cluster centroid and then recalculating it based on new cluster assignments until convergence is reached.

Table 2: *GLCM features*

Feature	Numerical Values
Contrast	276.4203
Correlation	0.9806
Energy	0.5117
Homogeneity	0.8256

Table 2 displays GLCM features and their corresponding numerical values which are used to characterize the image texture. Contrast is a local variations in image whereas parallel measures the lined dependence of gray levels between adjacent pixels. Energy is also known as angular second moment elements in GLCM. Finally sameness events the familiarity of circulation of fundamentals in GLCM.

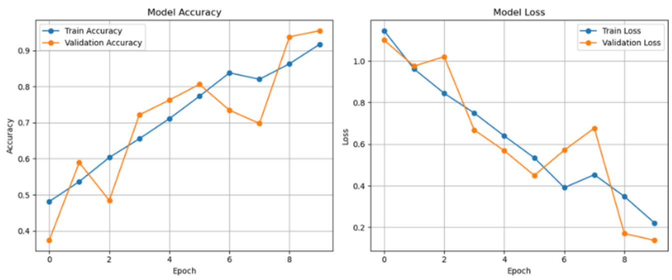

Figure 11: *Model accuracy and model loss over Epoch*

Figure 11 represents the interpretation of model accuracy and model loss graph. The model accuracy shows the train accuracy and validation accuracy where blue line indicates accuracy model on training data. The orange line specifies accuracy of validation data. It also shows an upward trend with some fluctuations. The validation accuracy is slightly lower than training accuracy for most Epochs. Corresponding model loss graph shows train loss and validation loss similar to accuracy. Train loss indicates a downhill tendency, specifying the model is effectively falling its error on the training data during training. Crucially, while the training loss consistently decreases, the validation loss shows a slight increase after Epoch 8 before dropping significantly at Epoch 9. Thus the model appears to learn effectively as both training accuracy increases and training loss decreases.

Table 3: *Classification report*

Dementia	Precision	Recall	F1 score	Support
Mild demented	0.99	0.98	0.98	209
Moderate demented	1.00	1.00	1.00	39
Non-demented	0.93	0.99	0.96	711
Very mild demented	0.98	0.90	0.94	507
Macro average	0.97	0.97	0.97	1466
Weight average	0.96	0.95	0.95	1466

Table 3. shows the classification report which delivers a complete evaluation of machine learning model's performance related to dementia stages. Precision processes the accuracy of positive calculations for each classes. Recall calculate model's skill to find the significant occurrences of each class. F1 score is a harmonic mean of precision and recall. Support indicates an real incidences of each class in dataset. Macro average calculates unweight mean of precision, recall and F1 score. Weighted average provides a extra realistic representation of overall performance in an imbalanced datasets. Accuracy is the overall ratio of properly foreseen comments to all total observations. The achieved overall accuracy is 95% respectively.

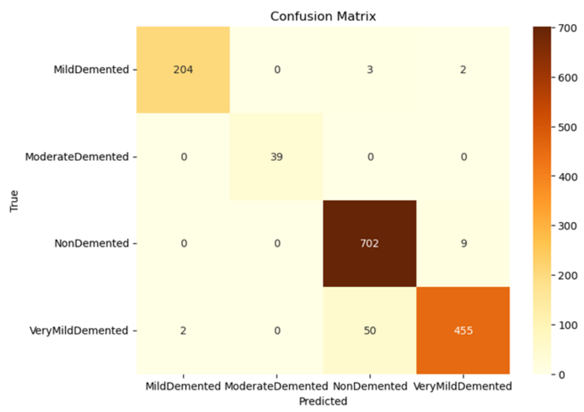

Figure 12: *Confusion matrix*

Figure 12 displays the confusion matrix of multi-class classification model of Alzheimer's disease based on the dementia stages. A confusion matrix table has rows, columns, diagonal and off-diagonal elements used to appraise the enactment by relating the predicted class labels with an real (true) class labels. The overall enactment of the model further umpired by manipulative metrics like accuracy, precision, and recall using the values from this matrix.

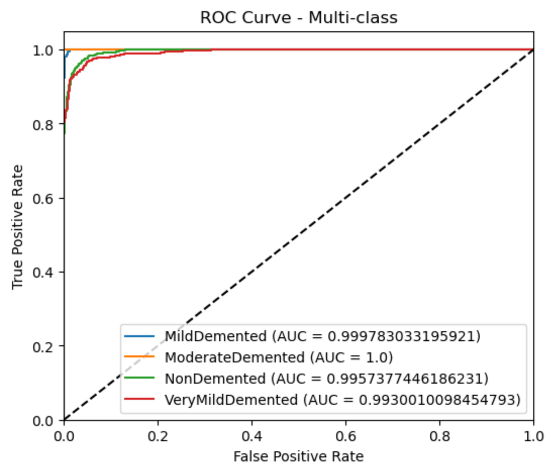

Figure 13: *Multi-class Receiver Operating Characteristic*

The interpretation of ROC and AUC curve is shown in figure 13. The Y-axis in the curve measures the proportion of actual positive cases while the X-axis measures proportion of real negative cases. The AUC is a value between 0 and

1 summarizing overall performance. The value of AUC near 1.0 indicates excellent discrimination, around 0.5 is no better than random and below 0.5 is worse than random. The high AUC values and ROC curves demonstrate the model's excellent discriminatory power across all measured dementia stages.

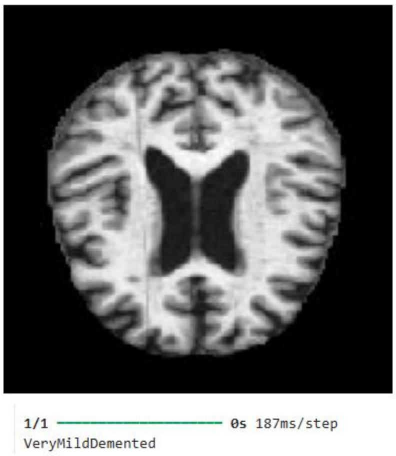

Figure 14: *Predicted output*

Figure 14 shows the predicted output. It shows very mild demented stage in early detection of Alzheimer's disease where structural changes associated with cognitive decline are present but are not yet severe.

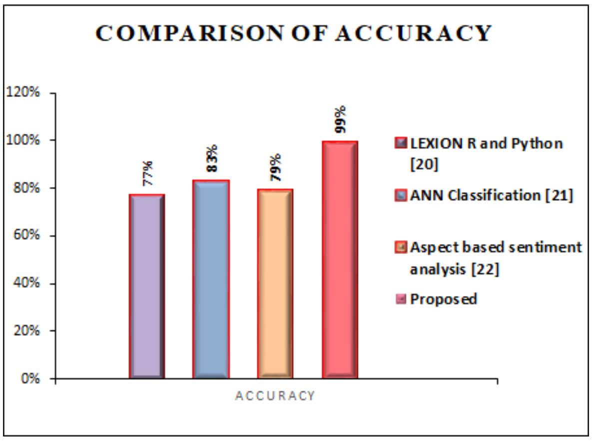

Figure 15: *Accuracy Comparison*

Figure 14 shows the accuracy comparison of various early detection methods for Alzheimer's disease. The 2D MRI- method [19] achieves about 85% and Machine learning based genetic data [20] obtained accuracy of 89%. Additionally a deep learning based image processing technique [21] attains 92%. Compared to all other technique the proposed scheme achieves about 95% accuracy respectively.

Table 4: *Comparative analysis of precision score of dementia*

Methods	Precision score
ML-Powered handwritten analysis [22]	97.44%
Machine learning and CNN on MRI datasets [23]	73.28%
Deep learning and SMOTE [24]	88.64%
Proposed	99%

Table 4 discuss the comparative analysis of precision score for various techniques involved in diagnosis of Alzhiemer's disease. Precision score that measures accuracy of positive forecasts prepared by a model. A higher score shows the method is more reliable. The ML-Powered technique [22] has a precision score of 97% of class 1 dementia. Likewise MRI dataset machine learning [23] has 73% of its precision score. Similarly the deep learning approach under SMOTE system [24] achieves 89% and the proposed technique records the precision score of 99% correspondingly.

6. Conclusion

This proposed research introduces a new method for the early detection of Alzheimer's disease using Temporal CNN. The objective of this paper is to capture various spatial and structural features of brain easing a inclusive investigation of Alzheimer. The k-means clustering algorithm to group the pixels of images into groups then the data attained at the output is loaded into a convolutional neural network using GLCM feature extraction. Consequently the predicted output by classifying the input data shows the signs of Alzheimer's disease, theoretically satisfying in early detection and invention strategies and the overall accuracy achieved about 95% and also the precision , recall scores are finely achieved about 96% *and* 95% Henceforth the proposed technique requires probable to support doctors and researchers in earlier Alzheimer's disease analysis.

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